(Online) ISSN 2303-4521
Periodicals of Engineering and Natural Sciences *Original Research*
Vol. 13, No. 3, July 2025, pp.551-560

Application of big data for the analysis and optimization of production lines

Zhibek Ussembayeva[1]*, Nurlan Dautkanov[1], Dinara Tlevlessova[2], Saltanat Mussayeva[3], Akmaral Mateyeva[4]
[1] Kazakh Research Institute of Processing and Food Industry, Almaty, Republic of Kazakhstan
[2] Almaty Technological University, Almaty, Republic of Kazakhstan
[3] South Kazakhstan University named after M. Auezova, Shymkent, Republic of Kazakhstan
[4] «BAYEL-KZ» LLP, Almaty, Republic of Kazakhstan

*Corresponding author E-mail: zh8886707@gmail.com

ABSTRACT

This research was prompted by the need for and rising interest in the expanding use of big data analytics to optimize production lines in the manufacturing business. The best method to improve productivity is to convert data into an achievable analysis. Production processes are growing increasingly complicated, arising from increased demands. Manufacturers of various sorts of goods are discovering substantial value in big data. The use of big data technologies in production lines and beyond is a recent multidisciplinary study integrating advanced computational analysis. The article gives insights into expanding real-time data analysis skills across numerous industrial industries by presenting a detailed assessment of big data technology and data analytics approaches. Using numerous case studies, this article analyses the vital role and advantages that big data analysis and optimization give manufacturers in increasing the efficiency and productivity of production lines in manufacturing.

Keywords: Big data, Industry 5.0, Optimization, Data analytics, Manufacturing, Production lines

1. Introduction

Production and manufacturing have progressed from Industry 1.0 to 4.0 over a century. Industry 4.0 emerged in 2011 with intelligent production for generations to come. The primary goal was to enhance output and maximize productivity using developing technology. Industry 5.0 is a forthcoming transformation aimed at harnessing the creativity of human professionals in collaboration with advanced and precise technology [1]. The Industry 4.0 standard has transformed the industrial industry via the integration of several technologies, including artificial intelligence (AI), Internet of Things (IoT), cloud computing, cyber-physical systems (CPSs), and intelligent computing [2]. The fundamental premise of Industry 4.0 is to render the production sector "intelligent" by interlinking equipment and gadgets that autonomously regulate one another. Industry 4.0 primarily focuses on process automation, minimizing human involvement in production operations [3]. It also emphasizes enhancing large-scale manufacturing and performance by facilitating machine learning [4] intelligence among devices and applications. Transformation of data into realizable objectives is the optimal method to enhance production. The production procedures are becoming more sophisticated owing to rising demands. Production firms utilizing such data for optimization will become more productive [5]-[7]. Big data frequently involves excessive data that traditional tools cannot collect, organize, handle, and evaluate promptly [8, 9] (see Figure 1).

Figure 1. Big data characteristics

Manufacturers of various sorts of goods are discovering substantial value in big data. With this rise, experts from numerous organizations began to comprehend the merits of implementing big data principles. The collection and analysis of data for improving business processes is not a new concept; it has existed since the late 20th century. The distinction is that data can be easily obtained and presented more appealingly for anybody to understand and utilize advantageously. Big data provides manufacturers with various tools to enhance operations and extract value from their assets, including predictive equipment maintenance and quality control.

In manufacturing, big data refers to the vast amounts of data produced throughout the production cycle by sensors, equipment, processes, and people [10]. Production monitors and enterprise resource planning (ERP) systems, including end-users' feedback, are among the various sources of this data.

These might be unstructured data like audio, video, text, or arranged like numbers and categories. Big data's value comes from its ability to compile information and highlight trends and insights absent from more traditional data analysis. Complex and dynamic manufacturing environments with many elements influencing production, quality, and efficiency abound [11].

Big data assists firms in being more proactive in their decision-making process. By embracing data-driven insights, firms can foresee issues, boost agility, and stay competitive in the face of ever-changing market needs. Volume, variety, and velocity were the three basic ideas that were first linked to big data [12]. Sampling issues arise when analyzing large amounts of data, while before, observations and samples were possible only. Therefore, the number four concept "honesty" is directly linked to the data value [13].

Big data veracity may involve costs and risks, preventing a firm from exploiting its potential value [14]. In the big data concept, unstructured data is the most widely used [15]. From 13 years ago, the "size" of big data has phenomenally grown to over hundreds of terabytes [16]. Identifying patterns from data sets requires several techniques and innovations [17].

1.1. Literature review

1.1.1. Major advantages of big data in production

The incorporation of massive volumes of data in manufacturing delivers a variety of transformational advantages. It may profoundly revolutionize how firms run their activities, increase the value of manufactured goods, and maximize resources. Using various technologies to acquire industrial data may enhance manufacturing processes in a few different ways. Significant benefits are described below.

Optimizing operational efficiency

Big data helps manufacturers better understand their daily activities, assisting in discovering problems and optimizing processes. By reviewing real-time data from manufacturing processes and equipment monitors, including worker behaviors, firms may identify hidden obstacles and prospects for progress.

With the utilization of big data analytics and real-time data, manufacturing companies can achieve robust production routines, resulting in improved productivity in production lines. Non-optimal or underutilization of production machinery or equipment may be identified with manufacturing data. Hence, production managers can maximize productivity in the manufacturing process.

Improving product quality & consistency

Advanced big data analytics and soft sensor applications in manufacturing may unravel hidden trends and patterns that impact vital production factors such as quality and consistency. Data analytics are vital in optimizing the production process by activating real-time and timely interventions, avoiding seemingly minor errors escalating into catastrophic failures or costly production shutdowns. Also, big data analytics strives to ensure uniformity of product quality irrespective of location, by standardizing production procedures across several production facilities or lines. Thus, big data analytics aid production firms in attaining and maintaining consistency and optimal quality standards.

Cost reduction and resource optimization

Optimal utilization of economic resources while minimizing production costs is the desired aim of every production company. Through practical and regular resource monitoring, production managers may minimize wastage. Big data utilization and application of advanced data analytics results in efficient energy consumption via the analysis of consumption trends and rectifying procedures appropriately. Data analysis assists production firms in estimating demand more accurately, avoiding product shortages or overproduction. Manufacturing firms may reduce emergency repairs or shutdowns and elongate the equipment life cycle if they adopt predictive rather than reactive maintenance.

Data from the production process may assist in cutting down on expenditures by revealing resource waste. Examples include personnel utilizing unnecessary materials in production and needlessly protracted equipment downtime. Manufacturing data may also improve product quality, saving costs since things will be less likely to be rejected in the assembly line or returned by consumers. In addition, production data will assist in enhancing the company's inventory levels, saving expenditures. For example, statistics may suggest that the firm's assembly lines are generating more things than the company will sell.

Improved customer service

Manufacturing data's potential to increase product quality may lead to stronger consumer interactions. Improved goods may lead to lower complaints, because consumers will be less likely to get a lousy product. In addition, production data helps inventory management, and better inventory management may also contribute to enhanced customer service. Supply chain management can estimate consumer demand based on peak seasons and guarantee that inventory levels meet customer demands. Manufacturing data may offer better insight into product delivery, including the shortest path to consumers.

1.1.2. Big data analytics tools and technology

Big data analytics consists of various technologies to manage and evaluate data. Several of them include:

1. Hadoop is an open-source system that effectively stores and analyses massive datasets on clusters of commodity hardware.
2. NoSQL stands for “not only Structured Query Language (SQL)”, and these databases can handle a range of data models.
3. MapReduce is a vital part of the Hadoop architecture. Data is filtered to various cluster nodes using the first method of mapping and the second method of addressing a query using reduction.
4. A second component of Hadoop is YARN, an acronym for "Yet Another Resource Negotiator" that utilizes cluster management technologies.
5. The open-source Spark cluster computing framework provides an interface for programming whole clusters. Spark can perform computational tasks involving both batch and stream processing quickly.
6. Tableau is a comprehensive data analytics application that allows for the analysis, collaboration, sharing, and working together on big data discoveries.

Other big data techniques include machine learning, neural networks, generic algorithms, clustering, regression analysis, association rule learning, time series analysis, classification tree analysis, etc.

2. Research method

2.1. Role of big data in production

Big data improves production operations and plays a critical role in modern manufacturing. Key functions of big data in production are as follows:

2.1.1. Decision-making

The decision-making efficiency and precision separate production firms and make them distinct. Using big data in predictive analytics assists production companies in making informed choices, aligning responses to demand fluctuations, and strengthening production preparation. Using big data technologies with complete data visualization and analytical capabilities in manufacturing helps production managers acquire actionable data to make informed choices and achieve operational success.

2.1.2. Enabling innovation

Based on real-time data, data scientists can apply big data and data analytics to stimulate innovation by deciphering consumer preferences and market trends, enabling production firms to produce new products and distinct services. Also, applying big data and data analytics in analyzing supply chain data enables firms to identify risks, efficiently manage inventories, optimize production and attain a robust supply chain.

2.2. Hurdles in the utilization of big data in production

Despite the enormous merits of big data and data analytics in production, their applications in this area are usually challenged. These hurdles generally originate from the intricacies of industrial settings and the system required to support big data projects. Significant problems in manufacturing include the following:

- Data integration poses a significant difficulty in manufacturing, since organizations typically gather and combine data from numerous sites, which may be hindered by old and outdated software.
- Technical expertise – skilled data science and analytics staff are crucial when moving deeper into data analytics. This might necessitate expenditures in training or employment to address the deficiencies in competence.
- Start-up expenses – acquiring technical expertise is a hurdle for most production firms, especially smaller ones, from adopting big data technology. Many production firms also face the problem of data integration due to incompatible technology. Most firms also lack employees with the skills and competence to understand and apply big data and data analytics.

2.3. Big data utilization in production

Big data finds application in a broad and varied spectrum within and outside the manufacturing sector. Big data and advanced data analytics technologies assist manufacturers in the optimization of resources like raw materials, water and even personnel, thereby reducing waste and idle time. These technologies also align with increasing customer preference and regulatory compliance requirements for eco-friendly products and procedures. The optimization offered by big data and data analytics also results in substantial cost savings and enhanced product quality from better responsiveness and production process efficiency.

2.3.1. Predictive maintenance

Big data plays a significant role in the area of reliability in the production sector. Reliability as a field of study highlights the importance of predictive maintenance in the production process. Regular and consistent collection and analysis of data from equipment monitors and sensors may aid production managers in forecasting the incidence of faults or repairs in a machine, thereby enabling manufacturers to rectify faults before they create significant disruptions.

2.3.2. Quality control and assurance

Big data and data analytics can ensure quality control and assurance sustenance. Real-time data scrutiny and evaluation by production managers across several production sites may aid manufacturing firms in detecting patterns and anomalies that may raise quality concerns.

2.3.3. Demand forecasting and market adaptation

Using data analytics and big data to analyze production data, specifically in market circumstances, seasonality, and customer preferences, may influence manufacturers to adjust their production and inventory plans accordingly, allowing for more flexible and responsive production processes. Precise demand prediction is fundamental for production firms aiming to remain competitive in an ever-evolving industry; hence, big data helps production firms forecast future demand patterns closely.

2.3.4. Energy management and sustainability

With rising pressure to embrace more sustainable practices, big data is helping industries lessen their environmental impact. By evaluating energy consumption trends across manufacturing sites, firms may find areas of inefficiency and apply adjustments that minimize energy use.

2.3.5. Custom product design and manufacture

The increased emphasis on customizing products for the customer, including the transition to an utterly consumer-driven manufacturing, is one of the contemporary challenges facing the manufacturing industry. This is challenging because it suggests further tooling or machine adjustments that might unintentionally result in more production downtime. Big data may answer this problem as businesses use big data analytics to map customer behavior using sophisticated forecasting and predictive modelling tools, setting up their production line to increase order fulfilment efficiency.

2.3.6. Supply chain management

Big data assists production in reducing manufacturing supply chain risks. An organization may predict the likelihood of on-time delivery in advance by analyzing several external factors that affect the traffic on transit routes. It would enable a manufacturing company to proactively create backup plans to lessen the impact of these factors on production.

2.3.7. Preventive maintenance

Big Data analytics can now identify in-line equipment production output, enabling production firms to standardize all machines ' operations. This makes it easier for manufacturers to prevent malfunctions and downtimes.

2.4. Optimizing big data in manufacturing

Researchers are becoming more interested in studying real-time optimization models in manufacturing and production to increase the efficiency of the production processes. The use of modelling and simulation is growing in developing real-time industrial control systems, where sensors and radio frequency identification (RFID) tracking devices provide an adequate and reliable real-time data source. To accurately predict direct food production and market demand, [18] used a Bayesian network to create a cause-and-effect relationship between the data. One of the reasons is that domain-related research articles are few, and predictive analytics has become commonplace in most areas. This is not to say that predictive analytics is no longer relevant. [19] provides a summary of supply chain predictive big data analytics (BDA), which includes trend analysis, demand forecasting, and customer analysis. Demand forecasting in closed-loop supply chains is one area that needs both study and practice. Similarly, combining IoT devices with analytical and artificial intelligence techniques has great potential. Collecting industrial data may assist in optimizing operations, decreasing costs and enhancing customer service. Supply chain management should select the appropriate data-gathering solutions for their firm to guarantee that their organization benefits from the information. The technologies for gathering manufacturing data include IoT sensors, RFID tags, digital twins, industrial robots, smart cameras and AI. All may provide greater insight into a company's production line operations.

2.5. Key technologies for manufacturing data collection

Here are six of the most excellent solutions for gathering industrial data.

2.5.1. IoT sensors

IoT-enabled sensors allow providers to gather and analyze data throughout their manufacturing activities. IoT sensors are highly beneficial due to the following factors:

- The simplicity of installation, maintenance and replaceability.
- The vast variety of data that IoT-enabled devices can measure.
- The real-time aspect of data acquisition.
- The flexibility to tailor data collection depending on individual industrial demands.

2.5.2. RFID tags

RFID tags assist suppliers in monitoring the number of assets and the assets' whereabouts in their production facilities. When a particular sensor pings an RFID tag, the tag sends information on the amount and physical position of the object to which the RFID tag is connected. Manufacturers may use RFID tags to monitor the following data:

1. The location of particular machinery and handling equipment, such as replacement manufacturing line machines, forklifts and autonomous robots.
2. The placement of inventories and supplies for the manufacturing process.
3. The stock levels of raw materials and components.

The speed with which RFID tags can give information about the positions of assets might assist in decreasing production delays.

2.5.3. Digital twins

Digital twins allow suppliers to represent the essential features of their manufacturing processes in a digital system. For example, a factory may establish digital twins for its end-to-end manufacturing lines to collect information about its production lines' inputs, assembly and outputs. These digital representations allow producers to create and test numerous setups and situations without making potentially expensive real-world adjustments. Digital twins may assist in streamlining manufacturing operations and allow predictive maintenance. Manufacturers may also integrate the technology with other data-gathering technologies, such as IoT sensors, to monitor performance.

2.5.4. Industrial robotics and automation sensors

Internet of things (IoT) sensors are excellent for monitoring many manufacturing process elements, but built-in sensors are much better for deep data collecting and analysis. These preinstalled sensors may assist in discovering data such as variances in machine tolerances, product quality and uniformity, and the need for preventive maintenance. These sensors can transmit data between robots and machines and modify equipment operations to enhance efficiency if required.

Built-in sensors perform effectively as part of a collaborative technology strategy. For example, separate robots may utilize their sensors to work as a fleet, making real-time choices to optimize production inputs and outputs.

2.5.5. Smart cameras and computer vision

Computer vision and smart cameras are modern sensors that visually monitor individual products and the whole production line, allowing an intimate study of any phase of the manufacturing process. Computer vision may help enhance worker safety and eliminate bottlenecks by recognizing issues before delays arise.

Smart cameras are also beneficial for quality monitoring and achieving production requirements. Manufacturers may integrate smart cameras with other technology to provide notifications about issues with goods and automated rejection of faulty items.

2.5.6. Artificial intelligence

AI can assess production data in real time and, in certain situations, modify based on those results. AI and machine learning can carry out the following tasks:

- Identify trends in production data, then flag any possible difficulties.
- Forecast future situations and identify possible dangers.
- Align supply, demand and capacity planning to improve throughput.
- Optimize production processes utilizing historical data.
- Identify the necessity for preventive maintenance.

More excellent data collection offers more insight from machine learning. Manufacturing supply networks are complicated, and big data analytics help firms better understand how they function. Machine learning and big data analytics provide firms with competitive advantage by supporting enhanced problem-solving in every field. It is also used for preventive equipment maintenance, such as spotting abnormalities before a breakdown.

3. Results

Crowd-sourced data on mobile network quality may give great insights and assist in uncovering network problems. Yet the amount of this data rises faster than most network analytics tools can manage. It might take analysts days of painstaking research to gain crucial insights from a dataset. At this size, it’s hard for these standard systems to view network abnormalities without shrinking or pre-aggregating, meaning critical insights are missing. Significant cases of significant data use in manufacturing include demand forecasting, supply chain optimization, quality control, manufacturing line improvement, customer data analysis, and price optimization. Below are the case studies used for this study.

3.1. Demand prediction to optimize the supply chain

A distributor of food products altered its supply chain during the COVID-19 pandemic in 2019 (COVID-19) by using demand predictions rather than historical data. The company collaborated with Accenture to develop an AI system that uses fresh data and modelling techniques to improve demand sensing. The business gained more knowledge and flexibility to anticipate supply chain disruptions by combining external data, such as weather and restaurant bookings, with internal data, such as sales and inventory. In addition to improving the distributor's supply chain management, the AI solution has made it more resilient to disruptions.

3.2. Cobots and autonomous mobile robots

According to Rockwell Automation's "9th Annual State of Smart Manufacturing" report, manufacturers have already embraced collaborative robots (cobots) and autonomous mobile robots (AMRs) to augment and enhance the workforce while lowering errors, speeding up time to value, and improving quality. Approximately 85% of those surveyed have invested in artificial intelligence/ machine learning (AI/ML) this year or plan to do so. With the help of more than 750,000 robots, including a brand-new robotic tool called Sequoia, Amazon claims to be able to identify and store goods in fulfilment centers up to 75% faster than it does now. Amazon said Sequoia improves shipment predictability and increases the quantity of items offered for same-day or next-day delivery by cutting down on order processing times via fulfilment centers by up to 25%. According to ABI Research, drones are becoming increasingly common in the industrial sector. [20].

3.3. Improving manufacturing processes

Big data may be used to collect and analyze process data to comprehend production unpredictability, quality concerns, production downtime, and other issues, leading to early diagnosis and cost savings.

For instance, in a McKinsey case study on the pharmaceutical sector, a business tracked the purity of its product (blood components and vaccinations) using 200 factors in live, genetically modified cells. In contrast to the others, they found that two batches of the product had between 50 and 100 percent variation. Big data analytics was used to identify nine criteria that were directly related to vaccine output. By altering specific target processes, the firm optimized these parameters and boosted vaccine production by 50%, resulting in yearly savings of almost $7.5 million.

4. Discussion

Manufacturing and production include the procedures of collecting, processing, analyzing, and visualizing essential data via technological techniques connected to machine learning. However, considerable data research might be challenging given how quickly technology develops. Few studies have attempted to address the optimization strategies in manufacturing and production lines by employing big data about supply chain activities, which include demand management, manufacturing, warehousing, logistics and transportation, and procurement [4], [6]. According to the study, not much is known about real-time optimization models to boost the efficiency of the logistics and manufacturing processes [4].

There is a paucity of research on how big data may be employed to optimize manufacturing and production lines. Noteworthy are the difficulties with privacy and the unwillingness to share genuine case studies, motivated by competing interests. The existing case studies show that big data applications have been employed successfully with Generative AI in CAD product design and documentation, resulting in greater flexibility and decreased machine performance mistakes.

The deployment of robots and AMRs by manufacturers has resulted in enhanced speed by as much as 75% and improvement in the quality of manufacturing. The use of AI in the supply chain of manufacturing led to the capacity of the producer to detect and forecast needs, culminating in more efficient supply chain management. Also, the McKinsey case study revealed that Big Data Analytics (BDA) led to an increase in productivity by 50% and savings of over 7 million dollars yearly.

The novelty of this study lies in its innovative application of advanced technologies, such as AI, machine learning and big data analytics, and not from historical data, to drive business value and improve manufacturing and supply chain management.

5. Conclusion

The era of big data is here. Data analytics is increasingly being used to inform business strategy and operational decisions. The top or leading manufacturers will use big data technology to expand their customer base internationally and benefit from this and many other sources. The lack of case studies and real-world examples is one of the main gaps in the current literature on big data management and optimization in production lines.

The justification is that there are several issues with using big data-related techniques for production line analysis and optimization. Improving the hardware and software setup to strike a balance between price and performance is one of the issues. It is expensive, time-consuming, and challenging to conduct empirical research to enhance the setup. Thus, simulation-based techniques are profitable [21].

Additional concerns include privacy, security, data quality, data collection continuity, data cleaning, and data standardization. Despite technology and data quality concerns, businesses mentioned cultural and administrative challenges as significant impediments [22]. However, the human skills and abilities business executives need to use big data are falling behind, even though the computer technology required to manage and optimize big data is improving. This is another significant problem in this industry [23].

There is a dearth of scientific papers offering real-world examples due to all these obstacles and corporate managers' lack of desire to promote their efforts in conferences and peer-reviewed journals. Maturity models may help companies close this gap by comparing their technological proficiency to industry standards and identifying the requirements for growing their big data projects.

The second strategy to address the challenge is for supply chain businesses to collaborate. Lastly, it is suggested that supply chain executives and academics work together to improve scholarly publications and increase the success of practical projects.

The focus of the few articles on using big data for production line analysis and optimization was on large corporations. Future research may concentrate on using big data to analyze and optimize production lines for micro and small businesses, since they might be more willing to share the results of their studies.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

Funding information

No funding was received from any financial organization to conduct this research.

Author contribution

The contribution to the paper is as follows: Zh. Ussembayeva, N. Dautkanov: study conception and design; D. Tlevlessova: data collection; X. Dautkanov, S. Mussayeva.: analysis and interpretation of results; A. Mateyeva: draft preparation. All authors approved the final version of the manuscript.

References

[1] K. R. M. Praveen, P. Quoc-Viet, B. N. D. Prabadevi, T. R. G. Kapal, R. Ruby, and L. Madhusanka, “Industry 5.0: A survey on enabling technologies and potential applications”, *Journal of Industrial Information Integration*, vol. 26, article 10025, 2022. https://doi.org/10.1016/j.jii.2021.100257

[2] M. Ryan, “Agricultural big data analytics and the ethics of power”, *Journal of Agricultural and Environmental Ethics*, vol. 33, pp. 49-69, 2020. https://doi.org/10.1007/s10806-019-09812-0

[3] M. N. O. Sadiku, T. J. Ashaolu, A. Ajayi-Majebi, and S. M. Musa, “Smart factory: a primer”, *International Journal of Scientific Advances*, vol. 2, no. 1, pp. 1-4, 2021. https://doi.org/10.51542/ijscia.v2i1.1

[4] L. Kirichenko, O. Pichugina, T. Radivilova, and K. Pavlenko, “Application of Wavelet transform for machine learning classification of time series”, *Lecture Notes on Data Engineering and Communications Technologies*, vol. 149, pp. 547-563, 2023. https://doi.org/10.1007/978-3-031-16203-9_31

[5] A. Idrees, H. S. Fahimeh, A. Renu, K. B. S. P. Gnana, and P. Mukesh, “Big data optimisation and management in supply chain management: a systematic literature review”, *Artificial Intelligence Review*, vol. 56, no. S1, pp. 253-284, 2023. https://doi.org/10.1007/s10462-023-10505-4

[6] K. Govindan, T. Cheng, N. Mishra, and N. Shukla, “Big data analytics and application for logistics and supply chain management”, *Transportation Research Part E-Logistics and Transportation Review*, vol. 114, pp. 343-349, 2018. https://doi.org/10.1016/j.tre.2018.03.011

[7] T. Nguyen, L. Zhou, V. Spiegler, P. Ieromonachou, and Y. Lin, "Big data analytics in supply chain management: a state-of-the-art literature review", *Computers & Operations Research*, vol. 98, pp. 254-264, 2018. https://doi.org/10.1016/j.cor.2017.07.004

[8] F. Cappa, R. Oriani, E. Peruffo, and I. McCarthy, "Big data for creating and capturing value in the digitalised environment: unpacking the effects of volume, variety, and veracity on firm performance", *Journal of Product Innovation Management*, vol. 38, no. 1, pp. 49-67, 2021. https://doi.org/10.1111/jpim.12545

[9] R. Cepero "5 Biggest data challenges", *Bieuwire*, Dec. 29, 2019. [Online]. Available: https://bieuwire.com [Accessed: June 1, 2025]

[10] A. D. S. Jain, I. Mehta, J. Mitra, and S. Agrawal, "Application of big data in supply chain management", *Materials Today Proceedings*, vol. 4, no. 2, pp. 1106-1115, 2017, https://doi.org/10.1016/j.matpr.2017.01.126

[11] L. Abualigah, "Enhancing Real-Time Data Analysis through Advanced Machine Learning and Data Analytics Algorithms", *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 21, no. 1, pp. 4-25, 2025. https://doi.org/10.3991/ijoe.v21i01.53203

[12] A. McAfee, and E. Brynjolfsson, "Big data: the management revolution", *Harvard Business Review*, vol. 90, no. 10, pp 60-66, 2012. https://hbr.org/2012/10/big-data-the-management-revolution

[13] M. Adhikari, "The 5 V's of big data - Watson Health Perspectives", *Deepstash*, Dec. 17, 2021. [Online]. Available: https://deepstash.com/article/113400/the-5-vs-of-big-data-watson-health-perspectives [Accessed: June 1, 2025]

[14] M. Hilbert, and P. Lopez, "The world's technological capacity to store, communicate, and compute information", *Science*, vol. 332, no. 6025, pp. 60-65, 2011. https://doi.org/10.1126/science.1200970

[15] N. Dedić, and C. Stanier, (2017). "Towards differentiating business intelligence, big data, data analytics and knowledge discovery", In *Proc. 5th International Conference*, 2017, vol. 285. pp. 114-122. https://doi.org/10.1007/978-3-319-58801-8_10

[16] S. Everts, "Information overload", *Distillations*, vol. 2, no. 2, pp. 26-33, 2016.

[17] I. A. T. Hashem, I. Yaqoob, N. B. Anuar, S. Mokhtar, A. Gani, and S. U. Khan, "The rise of 'big data' on cloud computing: Review and open research issues", *Information Systems*, vol. 47, pp. 98-115, 2015. https://doi.org/10.1016/j.is.2014.07.006

[18] G. Ji, L. Hu, and K. H. Tan, "A study on decision-making of food supply chain based on big data", *Journal of Systems Science and Systems Engineering*, vol. 26, no. 2, pp. 183-198, 2017. https://doi.org/10.1007/s11518-016-5320-6

[19] M. Seyedan, and F. Mafakheri, "Predictive big data analytics for supply chain demand forecasting: methods, applications, and research opportunities", *Journal of Big Data*, vol. 7, no. 1, article 53, 2020. https://doi.org/10.1186/s40537-020-00329-2

[20] E. Shein, "AI use cases in manufacturing", *Techtarget*, Oct. 07, 2024, [Online]. Available: https://www.techtarget.com/searcherp/feature/10-AI-use-cases-in-manufacturing [Accessed: June 1, 2025]

[21] S. Tiwari, H. M. Wee, and Y. Daryanto, "Big data analytics in supply chain management between 2010 and 2016: insights to industries", *Computers & Industrial Engineering*, vol. 115, pp. 319-330, 2018. https://doi.org/10.1016/j.cie.2017.11.017

[22] D. Arunachalam, N. Kumar, and J. P. Kawalek, "Understanding big data analytics capabilities in supply chain management: unravelling the issues, challenges and implications for practice", *Transportation*

Research Part E: Logistics and Transportation Review, vol. 114, pp. 416-436, 2018. https://doi.org/10.1016/j.tre.2017.04.001

[23] M. W. Barbosa, A. De La Calle Vicente, M. B. Ladeira, and M. P. V. Olivera, “Managing supply chain resources with Big Data Analytics: a systematic review”, *International Journal of Logistics Research and Applications*, vol. 21, no. 3, pp. 177-200, 2018. https://doi.org/10.1080/13675567.2017.1369501